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Abstract

Threat maps are an important tool for identifying locations where both threatening agents and conservation assets overlap in space. Such information is typically used in the identification of priority locations for conservation action. When threats are invasive species, one common method is to overlay the modelled distribution of an invasive species with that of conservation assets, assuming that spatial overlap relates to impact, however, this assumption is often faulty. We propose that the magnitude of a threat, rather than the distribution of invasive species, should be modelled directly, based on a mechanistic understanding of the how invasive species impact conservation assets. This novel approach was applied to the case of feral pigs (Sus scrofa) one of the world's worst invasive species. In Hawaii, feral pigs impact threatened plant communities through direct disturbance and act indirectly as vectors for weed dispersal. We collected occupancy data on the island of Oahu using detection data from remote camera traps and disturbance surveys. These data were used as the response variables in a model that acts as a surrogate for magnitude of threat impact on biodiversity, and thus identifies locations where pigs are likely to have the greatest impacts on threatened plants. Observed and predicted disturbance each correlated with the number of camera detections of pigs, indicating that both metrics are likely predictors of impact on threatened Hawaiian plants. This approach provides a new method for the creation of threat maps calibrated with likely impact for use in conservation prioritizations, using commonly implemented monitoring techniques for feral pig globally.

Keywords	threat map; conservation planning; invasive species; feral pig; remote camera; impact evaluation
Taxonomy	Invasive Species, Conservation Planning, Conservation Ecology

Corresponding Author	Jeremy Ringma
Corresponding Author's Institution	The University of Hawaii
Order of Authors	Jeremy Ringma, Melissa Price

Suggested reviewers	David Ramsey, Nancy Auerbach, Thomas Gillespie

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March 16, 2016

Dear Editors,

Threat maps are an important tool in conservation for identifying and visualizing the spatial distribution of invasive species and other threatening agents. In the recent paper by Tulloch et. al. (2015), titled "Why do we map threats? Linking threat mapping with actions to make better conservation decisions", the authors highlighted the utility of threat maps, but recognized that they were often poorly incorporated, and should be considered within cost-effectiveness frameworks. For example, when considering the effectiveness of conservation action against threats such as invasive species, habitat suitability of the invasive species is often used as the threat layer, assuming a strong correlation between habitat suitability and impact on biodiversity. However, this is often not the case. Given that threat maps are often created through modelling approaches, alterations to modelling frameworks could better represent the true relationship between threats and their impacts to biodiversity.

In this paper we present a novel approach to modelling the distribution of a threat a threatening agent, feral pigs (*Sus scrofa*), and their impact on the island of Oʻahu in Hawaiʻi. In Hawaii feral pigs disrupt native vegetation through digging and browsing, and aid in the spread of invasive weeds. Modeling pig distribution alone through traditional approaches might underestimate impact to areas with soft soils or high precipitation, and overestimate impact in other areas We used a mechanistic understanding of the process of how pigs threaten plants to generate a threat map representing magnitude of likely impact. We used number of camera detections as a surrogate for impact, demonstrating a connection with pig disturbance throughout our modelling process.

Our approach of simulating magnitude of impact is broadly applicable to threat mapping generally, while our survey and modelling method can be used widely for pigs and similar invasive species. We hope you agree that our findings will be of interest to the broad conservation readership of *Biological Conservation*.

Regards

Jeremy Ringma

An impact-based approach to mapping threats from invasive species.

Jeremy Ringma, Melissa R. Price

The University of Hawaiʻi at Mānoa. Department of Natural Resources and Environmental Management

Abstract

Threat maps are an important tool for identifying locations where both threatening agents and conservation assets overlap in space. Such information is typically used in the identification of priority locations for conservation action. When threats are invasive species, one common method is to overlay the modelled distribution of an invasive species with that of conservation assets, assuming that spatial overlap relates to impact, however, this assumption is often faulty. We propose that the magnitude of a threat, rather than the distribution of invasive species, should be modelled directly, based on a mechanistic understanding of the how invasive species impact conservation assets. This novel approach was applied to the case of feral pigs (*Sus scrofa*) one of the world's worst invasive species. In Hawaiʻi, feral pigs impact threatened plant communities through direct disturbance and act indirectly as vectors for weed dispersal. We collected occupancy data on the island of Oʻahu using detection data from remote camera traps and disturbance surveys. These data were used as the response variables in a model that acts as a surrogate for magnitude of threat impact on biodiversity, and thus identifies locations where pigs are likely to have the greatest impacts on threatened plants. Observed and predicted disturbance each correlated with the number of camera detections of pigs, indicating that both metrics are likely predictors of impact on threatened Hawaiian plants. This approach provides a new method for the creation of threat maps calibrated with likely impact for use in conservation prioritizations, using commonly implemented monitoring techniques for feral pig globally.

1 Introduction

In the field of conservation science, threat maps are spatial representations of the distributions of threatening agents (Tulloch et al. 2015). Using threat maps, decision makers can make informed choices about the allocation of management resources based on their overlap with priority conservation assets (Auerbach et al. 2014), resulting in conservation actions with greater cost-effectiveness. This process is a more efficient form of prioritization for spatially explicit actions (Giakoumi et al. 2015), as it directly considers the effect of conservation actions explicitly within its framework (Game 2013), but to do so, spatial projections of threats must accurately portray this relationship.

A common application of threat maps is to compare the distribution of invasive species with that of the species they threaten (Phillips et al. 2003, Molnar et al. 2008, Evans et al. 2011). Hence, creating a threat map typically involves some form of species distribution modelling for both threats and conservation units (Higgins et al. 1999, Auerbach et al. 2014). However, this operates under several assumptions that should be shown to be accurate before prioritizing management actions in these areas. Firstly, the predicted suitability or occupancy of habitat by invasive species must scale proportionately with its impact on biodiversity. Secondly, uncorrelated spatial covariates must not influence this interaction, i.e. modelled suitability of the threatening agent must consistently impact biodiversity across space. Verifying these assumptions demands a detailed understanding of community interactions across geographic space, requiring a more detailed model of system dynamics than typically available.

An alternative process would directly model the distribution of mechanism by which invasive species impact biodiversity, and compare this with the distributions of conservation assets. While conceptually simpler, this approach requires a clear, mechanistic understanding of the interaction between the threatening agent and conservation asset, and an understanding of what type of data must be collected for predictive models. The model created is also bespoke to that specific interaction.

1.1 Feral pig management on Hawaiian Islands

Polynesian and European colonization of the Hawaiian Islands resulted in the introduction of numerous threatening processes such as deforestation (Rolett and Diamond 2004), watershed disturbance (Woodcock 2003) and a host of invasive species (Miller and Eldredge 1996, Gillespie et al. 2008). As a result, Hawaii now hosts the highest proportion of threatened species of any state in the United States of America (Dobson et al. 1997). Among the most damaging threatening agents to Hawaiian biodiversity are feral pigs (*Sus scrofa*). Feral pigs disturb remnant vegetation through foraging, and aid the spread of invasive weeds through their movements (Nogueira-Filho et al. 2009). Their digging accelerates erosive processes, damaging watersheds and water quality (Barrios-Garcia and Ballari 2012), and may aid the spread of avian malaria through the creation of mosquito breeding habitat (Samuel et al. 2011).

Feral pigs present a threat to ecosystems around the globe, however, unlike other locations where pigs are controlled through poison baiting (Cowled and O’Connor 2004) or eradicated island wide (Cruz et al. 2005, Parkes et al. 2010), feral pigs in Hawaii are also promoted as a valuable game species (Stone 1985, Kirch and O'Day 2003, Nogueira-Filho et al. 2009). As a recognized game species and environmental pest, Hawaiian government agencies are left with the conflicted objective of both controlling pig numbers for environmental purposes and their promotion for hunting. As a compromise, the use of exclusion fencing to remove pigs from high-value conservation and agriculture areas by private, non-profit, federal and state managers has become increasingly popular.

On Hawaiian Islands, pigs are primarily managed by exclusion fences constructed in priority watersheds containing in-tact, native vegetation. However, like other forms of conservation fencing (Ringma et al. 2017) and protected area networks (Margules and Pressey 2000), Hawaiian pig exclusion fencing is arising in an ad-hoc manner. With the goal of an additional 100,000 acres of fencing to be constructed by 2030 (Governor of Hawaii 2016), prioritization of new fencing projects using decision science will likely improve the effectiveness of conservation action. Hawaiian biodiversity would indefinitely benefit from an impact evaluation approach (Pressey et al. 2015) by identifying locations where threatened plant communities are most impacted by pig disturbance.

Here we outline the process we adopted to create spatial estimates of likely feral pig impact on threatened plant communities on Oʻahu. We compare the model predictions made from camera trap data, cross-referenced against concurrent disturbance information and discuss how this approach might influence conservation decision making.

2 Methods

The mechanistic processes by which feral pigs impact conservation assets is through disturbance caused by (i) their digging and (ii) their assisted spread of competing invasive plants (Aplet et al. 1991). A threat map of likely impact of pigs on conservation assets needs to integrate both of these processes. Our conceptual model of pig impact relates to the level of pig activity at a site, where activity is a function of population density and frequency of habitat use. We estimated pig activity as inputs for our threat model using data from the two most commonly used feral pig survey techniques: (i) using remoted triggered camera traps and (ii) evidence of disturbance such as scat, tracks and digging: commonly referred to as “sign” (Holtfreter et al. 2008, Engeman et al. 2013). We cross references camera data with disturbance data to ascertain the relatedness of these two important factors, expecting data from the two survey methods to imperfectly correlate.

2.1 *Survey design*

Each site consisted of an array of six cameras (Bushnell Trophy Cams) distributed at regular 50 meter intervals. Cameras were programmed to take two consecutive images for each trigger and reset after three seconds. Sites were deployed for a two week period under one of two configurations depending on terrain: (i) a rectangular array, with cameras deployed in two parallel lines of three and (ii) a linear array, with all six cameras deployed along a transect. Linear arrays were deployed only in areas where topography did not allow for a rectangular array, such as on ridge crests with steep receding slopes on either side. Cameras were deployed in a manner that maximized the probability of detection, such as focused in a clearing, trail or area with obvious previous pig activity within a 10 meter radius of randomly pre-selected GPS co-ordinates. Cameras were attached to vegetation at approximately waist height on a roughly level trajectory with the ground. Camera data were viewed using VirtualDub 1.10.4. Photos containing images of feral pigs were filtered into a new database.

At each camera location, signs of pig disturbance were recorded in four 10x10 meter quadrats over a standardized two minutes search period for each quadrant. For linear arrays, quadrats were positioned along a line transect, while in rectangular arrays quadrats were located in a square configuration. In each quadrat we recorded the presence or absence of old and new signs of tracks, scat, digging and vegetation damage. New sign was defined as having likely occurred no more than two weeks prior. Disturbance surveys were conducted both upon the deployment and recovery of cameras from each site. Camera and vegetation data were collated into .csv files using Microsoft Excel.

2.2 Site selection

The island of Oʻahu was rasterized into 500x500 meter (25 ha) units using R packages raster (Hijmans 2016) and rgdal (Bivand et al. 2016). This size was chosen as it represents a likely home range size of pigs on Oʻahu (pers. comm. Chris Miller) and hence provides spatial independence among sites (home range may be larger in other areas and here sample units would need to be larger, see Caley 1997)). Potential survey sites were located at the centroid of each raster unit. The raster was masked to land recognized as a reserve using the Hawaiʻi state government reserve outline (State of Hawaii 2016). Remaining raster units were stratified by three altitudinal bands to prevent disproportionate sampling of the more frequent, low altitude raster units. Sample units were divided into three bands of 0-333, 334-666 and 667-1200 m. An equal number of were randomly drawn from these three altitude bands. The vegetation, slope, and topography of Hawaiian habitats make it difficult to access and deploy camera traps. When randomly-selected sites could not be reached, they were moved to the closest location that could be safely accessed.

2.3 Analysis

We wanted to generate a distribution model whose response layer could act as a reasonable surrogate for magnitude of feral pig impact of threatened Hawaiian vegetation. While (i) average number of pig detections was expected to be the best surrogate, other potential response variables included (ii) minimum estimate of unique individuals and (iii) unique events (summed one hour blocks in which pigs where detected on a camera), and disturbance data from the site, summarized as (iv) all new sign, (v) all old sign, and (vi) total sign (both old and new sign). Numerous environmental factors in Hawaiian ecosystems are strongly auto-correlated; hence a simple model with minimal predictive inputs was adopted to prevent over-fit (Guisan and Thuiller 2005). We used a mechanistic understanding of the relationship between pig activity and impact to determine the parameterization of our model, using only predictor variables likely to have a causative link with pig abundances. Annual rainfall (Giambelluca et. al. 2013), vegetation density and vegetation height were used as predictors (Giambelluca et. al. 2014). Zero-inflated models with Poisson distribution logit link correction factor were used to generate predictive models using R 3.3.2 (R 2016) and pscl (Jackman 2015). Zero-inflated models were chosen due to imperfect detection resulting in false absences in our dataset (Wenger and Freeman 2008). Non-significant terms were kept in the model if model fit from AIC was better with their inclusion.

3 Results

In total, data were collected from 28 sites in a three month period between June 13 and September 18, 2016. Pigs were captured on camera traps in 11 sites. For sites where pigs were detected, an average of 41±SE 12 photos per camera were captured over the two week sample period, with a maximum of 311 captures. Pigs were detected at all hours of the day, but were most active immediately after sunset, with a pronounced spike in activity between 1600 and 2100 hours. In comparison, sign was detected at 16 sites; pigs were detected at nine of these sixteen sites. Approximately six times more sign was detected at sites where pigs were captured on cameras, compared with sites where no pigs were detected by cameras (camera detection 6.36±SE 1.07, no camera detections 1.10±SE 1.35, $F = (1, 28) = 15.22$, $p<0.001$).

The average number of pig detections created a model with the strongest relationships (See Table 1 for significance values). Unique detection events formed a similar but weaker relationship, while minimum estimate of individuals did not produce significant relationships. New, old and total sign all produced models with significant relationships, and while rainfall do not form a significant relationship, it was retained as a predictor as AIC suggested greater model fit with its inclusion. Average number of pig detections (Figure 1) and total sign (Figure 2) were taken as the best models for camera data and disturbance data respectively. As expected, the average number of pig detections by camera and disturbance data formed significant but rough regressions. The correlative strength and deviance of camera and disturbance data remained consistent for both observed and predicted responses (Figure 3). The relationship between predicted camera and disturbance data was maintained across Oʻahu (linear regression, $F= (1, 28052) = 4.3e4$, $p<0.001$, $r^2 = 0.604$). Adding rainfall to the model explained nearly 13% of the remaining deviance (linear regression, $F= (2, 28051) = 3.8e4$, $p<0.001$, $r^2 = 0.732$).

4. Discussion

4.1 Impact based threat maps

Spatial allocation of management actions remains one of the primary gaps in conservation decision making (Game et al. 2013). While we have made significant progress on prioritizing protected areas under spatial frameworks (Margules and Pressey 2000), and prioritizing conservation action under cost-effectiveness frameworks (Joseph et al. 2009), we infrequently prioritize conservation action under spatial frameworks (but see Wilson et al. 2006). Threat maps provide a mechanism to assess the spatial variation in cost effectiveness of a given conservation action. However, threat maps are often poorly implemented (Tulloch et al. 2015), without a thorough understanding of how threats, biodiversity and managements interact, conservation planners risk identifying sub optimal management plans. Our strategy of using impact based threat maps improves the utility of threat mapping in conservation planning, because threat maps based on impact surrogates operate under fewer, more tenable assumptions about ecosystem interactions than threat maps based on species distribution models.

4.2 Camera detections as a surrogate for impact intensity

Camera traps are preferentially employed to estimate density surrogates, which may better reflect the activity level of pigs at a given site; however, it is pertinent to ensure that camera trap data at least reflects the observed disturbance. As expected, sign and camera detections roughly correlated while maintaining similar directionality (Figure 3), providing support for the hypothesis that camera detections acts as a surrogate for impact. While it is possible to generate a threat map for feral pig impact from disturbance data alone, population estimates based on disturbance data can differ from known population densities across environmental gradients such as rainfall and soil type (Massei et al. 1998) and is unlikely to capture the full extent of pig impact as a vector for weed dispersal. Improved model fit with the inclusion of rainfall data supports this finding, suggesting camera detections are likely to more accurately represent pig density and activity at the sample site.

4.3 Prioritizing management for feral pigs

Feral pigs are among the most damaging invasive species globally (Lowe et al. 2000). Their management has become an emerging priority in island (Roemer et al. 2002, Rouys and Theuerkauf 2003, Cruz et al. 2005, Nogueira-Filho et al. 2009) and mainland ecosystems (Lowe et al. 2000, Engeman et al. 2007, Doupé et al. 2010). However, the location of conservation action for feral pig management has been infrequently prioritized using systematic methods. Knowing the spatial distribution of pig impact is invaluable data for prioritizations and impact assessments. This approach provides a mechanistically grounded basis for predicting pig impact as inputs for threat maps using common survey techniques with broad application for both feral pig management, and as a basis for other invasive species.

Exclusion fencing is a pragmatic and often highly effective mechanism to protect conservation assets from the impacts of invasive species invasive species (Moseby and Read 2006, Doupé et al. 2010, Cole et al. 2012). However, fencing is a high cost management action, and at costs of up to $150,000 per kilometer, pig exclusion fencing in Hawaii is amongst the most expensive forms of conservation fencing globally (Long and Robley 2004). Systematic conservation planning can greatly improve the efficiency and effectiveness of fencing at fence networks (Bode and Wintle 2010, Bode et al. 2012, Helmstedt et al. 2014, Ringma et al. 2017), allowing for more accurate assessment of areas where threatened plant communities are most impacted by feral pig disturbance. To date, over 50,000 hectares of land on Hawaiian Islands has been fenced to exclude pigs for conservation reasons and over 100 km of pig exclusion fencing had been constructed on Oʻahu alone, with more planned in the future. Most fenced areas have been created either opportunistic or in an ad hoc manner. The creation of a threat map of likely feral pig impact allows for the identification of areas where remnant vegetation is at greatest risk allowing for greater cost-effectiveness of conservation action (see Auerbach et al. 2014).

5. Conclusions

Threat maps are an important tool for identifying priority locations for conservation actions, but suffer from shortcoming in representing how threat and biodiversity interact. Threat maps based on likely impact of the threatening agent can identify locations where conservation actions will be most cost effective. By collecting and cross referencing multiple sources of mechanistically grounded impact data, decision makers can have improved confidence that their impact model accurately represents the relationships between disturbance and threats.

6. Acknowledgements

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Table 1. Strength of model fit for each response variable. * indicate significance of relationships.

	Estimate	SE	Z value	P value
(i) Average detections				
Annual rainfall	-0.026	0.006	-4.179	<0.001 ***
Fractional vegetation	11.83	1.129	9.547	<0.001 ***
Vegetation height	-0.067	0.025	-2.726	0.006 **
(ii) Unique Individuals				
Annual rainfall	-0.013	0.012	-1.084	0.278
Fractional vegetation	-0.164	1.459	-0.112	0.910
Vegetation height	-0.052	0.045	1.150	0.249
(iii) Unique Events				
Annual rainfall	-0.013	0.008	-1.58	0.114
Fractional vegetation	2.444	1.208	2.023	0.043 *
Vegetation height	0.117	0.029	4.043	<0.001 ***
(iv) New Sign				
Annual rainfall	-0.0006	0	0	1.00
Fractional vegetation	11.51	3.864	2.981	0.003 **
Vegetation height	-0.183	0.081	-2.256	0.024 *
(v) Old Sign				
Annual rainfall	0.0006	0.021	0.032	0.974
Fractional vegetation	10.01	4.588	2.182	0.029 *
Vegetation height	-0.233	0.091	-2.572	0.010 *
(vi) All sign				
Annual rainfall	0.003	0.011	0.280	0.779
Fractional vegetation	10.28	3.355	3.064	0.002 **
Vegetation height	-0.136	0.051	-2.665	0.008 **

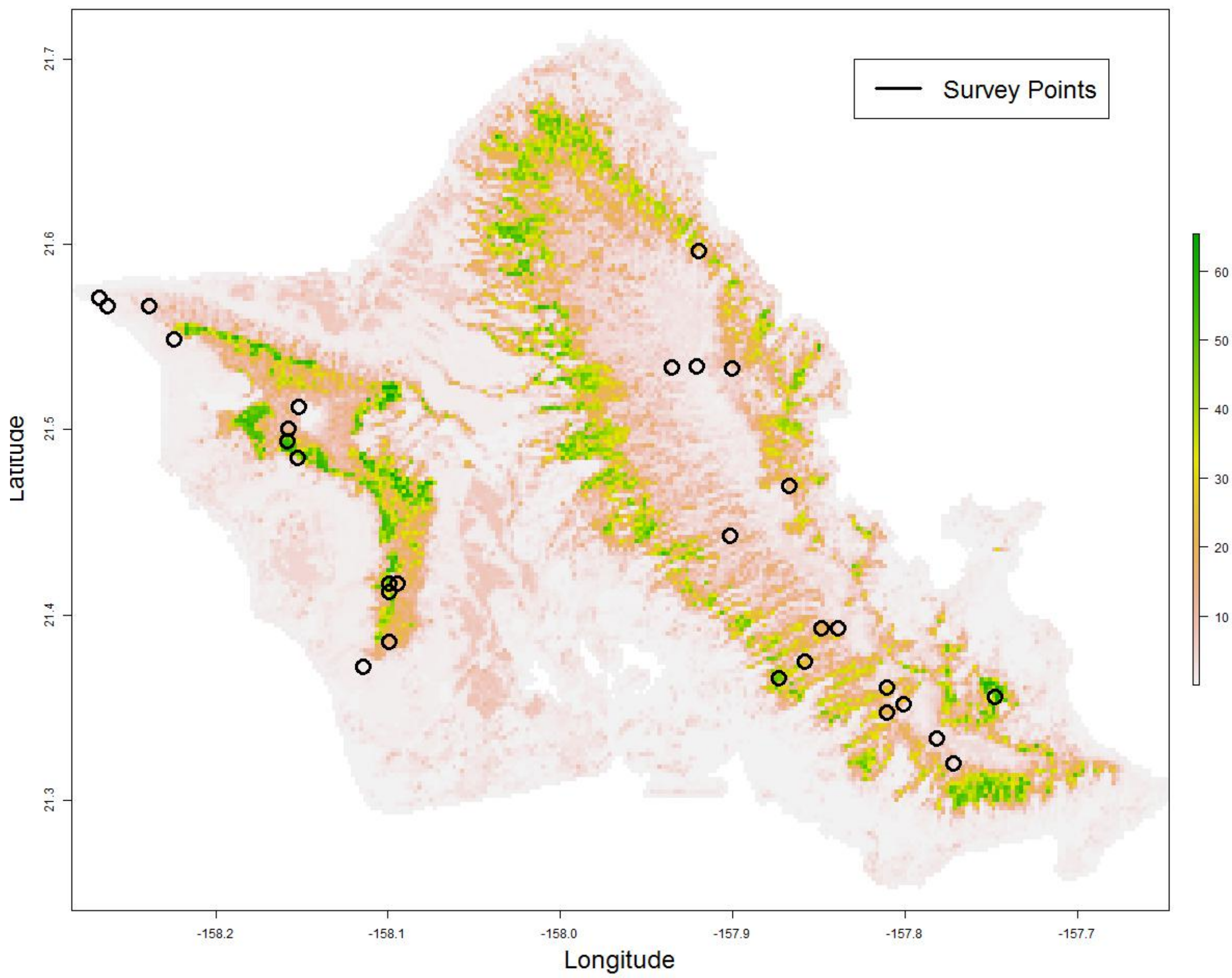

Figure 1. *The likely impact of pigs on O'ahu as predicted by the average number of camera detections per camera per site. Areas of highest impact are indicated in green. Black lines depict the location of survey sites.*

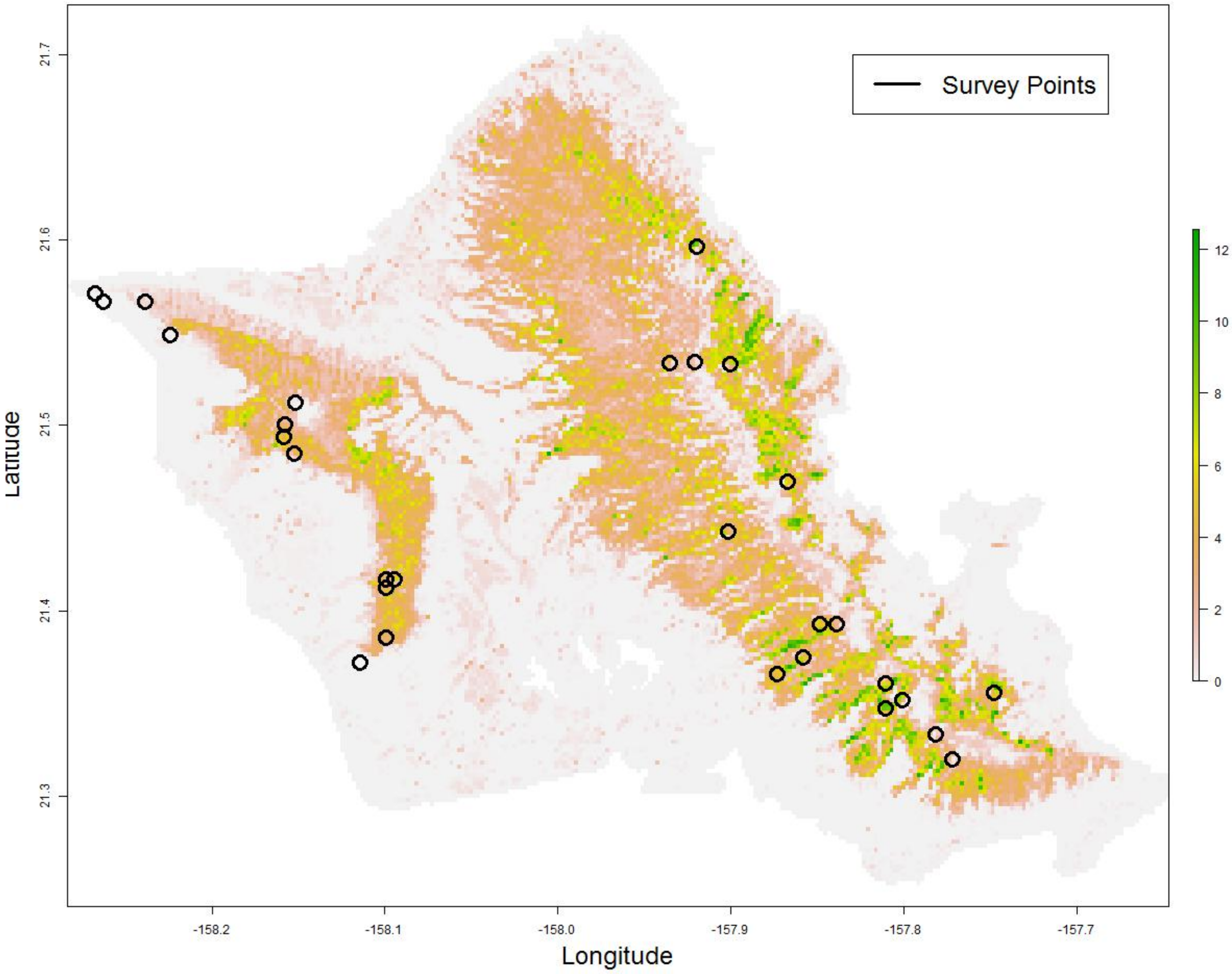

Figure 2. *The likely impact of pigs on O'ahu as predicted by total observed sign per site. Areas of highest impact are indicated in green. Black circles depict the locations of survey sites.*

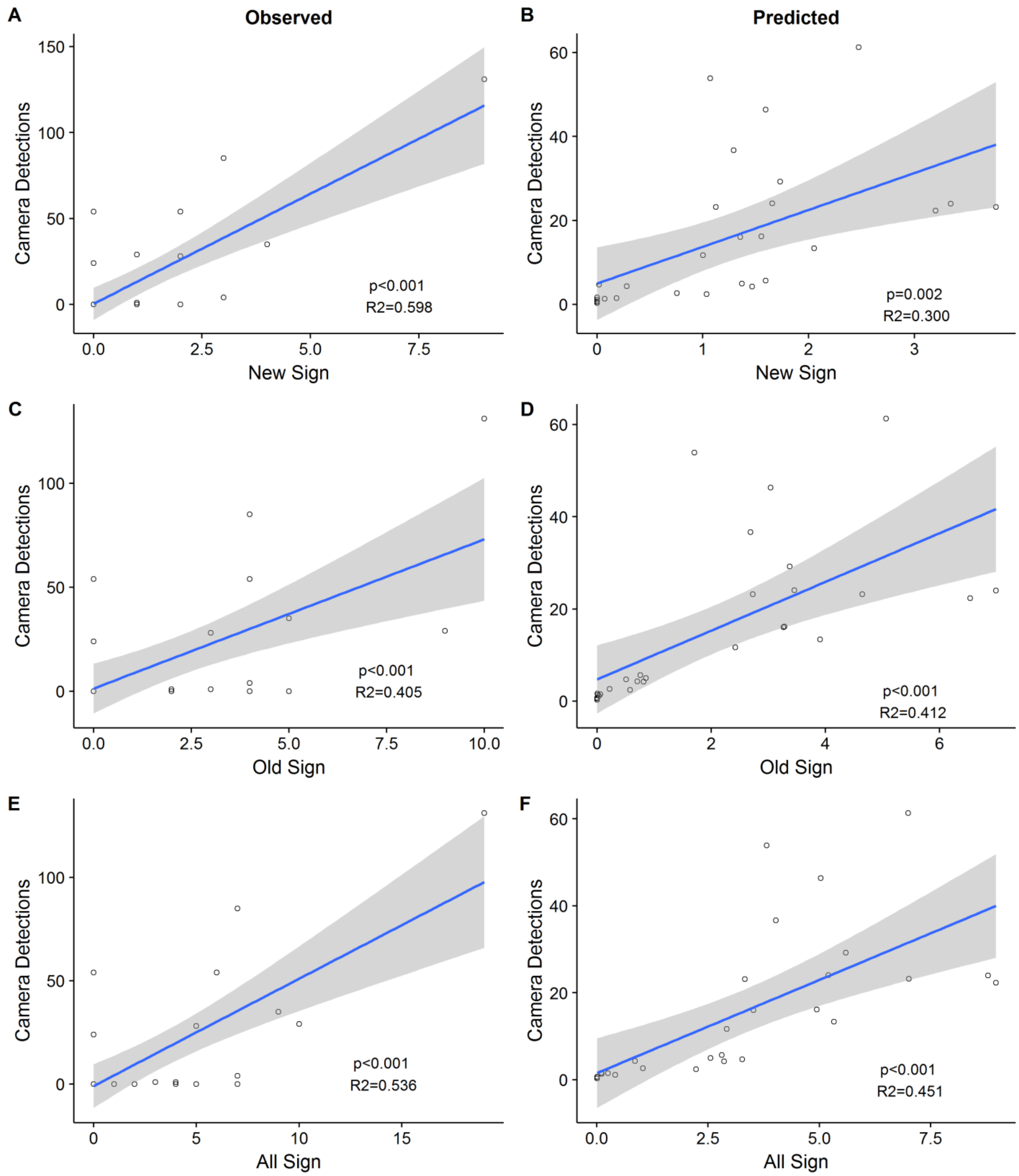

Figure 3. The relationship between number of camera detections and level of pig disturbances. The left hand "observed" column (A, C and E) depicts the relationship between observed disturbance and number of camera detections. The right hand "predicted" column (B, D and F) depicts the relationship between predicted disturbance at sample sites from our model and predicted camera detections.